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Study on Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract

An Adaptive Neuro- Fuzzy Inference System is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. In simple terms ANFIS is the data learning that utilizes fuzzy logic in order to transform the input to the output which is desired. This is done through highly interconnected Neural networks. This chapter presents Study on Adaptive Neuro-Fuzzy Inference System. In this study the prediction of shear contribution of FRP for the wrapped RC beams using an adaptive neuro-fuzzy inference system (ANFIS). In this study 7 internationally obtained guidelines are used for predicting the experiment result of the presented model. The result from this current study shows that the Adaptive Neuro- Fuzzy Interference System(ANFIS) can be used as the alternative for predicting the shear contribution of the FRP composite.

Keywords: *ANFIS, FIS, FRP composite, Fuzzy Logic, Fuzzy Model, Shear Contribution, Tensile strength.*

1. INTRODUCTION

An Adaptive Neuro- Fuzzy Inference System is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. This method was developed in the late 1980s. Since it integrates both neural and fuzzy network it has potential to benefit both in a single framework. In this study the prediction of shear contribution of fiber-reinforced polymers (FRP) for the wrapped reinforced concrete (RC) beams using an adaptive neuro-fuzzy inference system (ANFIS). For this proposal the training and testing of data of the ANFIS was done through 110 sets of database of the various literature published. The input of the ANFIS is includes the RC beams, concrete strength and some properties of the fiber-reinforced polymer such as its thickness, layers, strain, steel ratio, and the output for the ANFIS includes shear contribution of FRP. From several examination and analysis made with Adaptive Neuro-Fuzzy Inference System and the test results they both have correlated with each other. The present ANFIS is compared with the 7 prediction designed guidelines. From the result of the comparison it is found that the performance of the ANFIS was better in predicting the shear contribution of fiber-reinforced composites.

2. BASIC OUTLINE OF THE STUDY

The present research tries to explore the feasibility of ANFIS for predicting the shear contribution of strengthening the scheme of fiber reinforced polymer composites. The input of the ANFIS is includes the RC beams, concrete strength and some properties of the fiber-reinforced polymer such as its thickness, layers, strain, steel ratio, and the output for the ANFIS includes shear contribution of FRP.

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The predicted Fiber reinforced polymer composites of shear contribution was compared with the obtained FRP through experiments and also compared with 7 international acclaimed guidelines. The 7 predicted guidelines includes ACI, fib, CNR, DAfStb, CSA, TR-55 and JSCE. From several examination and analysis made with Adaptive Neuro-Fuzzy Inference System and the test results of FRP they both have correlated with each other. A study was conducted for investigating the influence of parameter of fiber reinforced polymer composites on shear contribution.

3. Adaptive Neuro-Fuzzy inference system (ANFIS)

3. 1. Basic concept

The fuzzy logic was established through the set of “Fuzzy theory”. This Fuzzy theory was considered as the foundation step for the Fuzzy logic methods, the fuzzy set was defined by the concept of MF (membership function) which is the value between numbers 0 and 1.0. With the concept of the MF, human knowledge can be transferred to the machine. The fuzzy logic is also known as the fuzzy model or fuzzy rule based model. The fuzzy rule-based model is considered as the subgroup of soft-computing.

The fuzzy interface system(FIS), consists of 5 parts

- A system based on rules (number of rules in fuzzy model)
- A database (definition of membership function is given based on fuzzy sets)
- A decision-making unit (executes the interface operation)
- A Fuzzification interface (conversion of inputs to the linguistic value)
- A De-fuzzification interface. (conversion of results to output)

Selecting the appropriate Fuzzy Interface System requires more knowledge about FIS and it would take considerable amount of time. An Artificial neural network is an easy computing technique which tries to reproduce the functional area of the biological neural network for engineering issues, and the it tries to make changes in the structural plan of the internal and external information during the learning process. The neural network which gains knowledge easily through back-propagation algorithm, at the same it takes more time for the learning process, analysing the trained network is comparatively tougher.

The ANFIS is hybrid system which is the combination of Artificial neural network and fuzzy logic system. So there are possibilities of ANFIS to have limitation of ANN and FIS and it must overcome its limitation to give a better system. The fuzzy model in the ANFIS is based on the rules of the input and output data.

3.2 ANFIS theoretical framework

The current study is the illustration of the Sugeno Fuzzy Model with x and y as inputs and f is considered as the output alongside with IF and Then fuzzy rules of Takagi and Sugeno is shown as

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$ (1)

Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$ (2)

Where p,q,r are the parameters. These parameters are user-defined and needs optimization under ANFIS training, A_1, A_2 is considered as the MF for input (x), B_1, B_2 is the MF for input(y) fig 6.1 shows the ANFIS model with inputs(x,y) and output(f). the nodes have similar function and described as follows. The node of layer 1 where i in this layer 1 is considered as the adaptive node and function of it is shown as

$O_{1,A} = \mu_{A1}(x)$ for i = 1, 2 (3)

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$O_{1,A} = \mu B_{t-2}(y)$ for i = 3, 4 (4)

Where $O_{1,i}$ is the output, i^{th} is the layer 1 node, x or y is the input, A_i or B_{i-2} is considered as the linguistic label.

In this study the Gaussian –shaped MF is used and function of it is shown as:

$$\mu A_i(x) = \exp\left(-\left(\frac{x-a_i}{b_i}\right)^2\right) \quad (5)$$

Where a_i & b_i is the width of the Gaussian MF, parameters are responsible for variation in Gaussian function, due to it many forms of membership function are displayed. These type of parameter are called as the premise parameter.

The output of layer 2 node is gained from incoming signal of the product which is shown as:

$O_{2,i} = w_1 = \mu_{Ai}(x)\mu_{Bi}(y)$ for i = 1, 2 (6)

Node of layer 3 is fixed and it is used for calculating firing strength of i^{th} rule to the sum of all firing rule which is shown as:

$$O_{2,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2 \quad (7)$$

Node of layer 4 is adaptive the function of it is shown as

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + \eta), \ for\ i = 1, 2 \quad (8)$$

The node in the layer 5 is based on the single circular node and the output is calculated from the income signals of layer which is shown as:

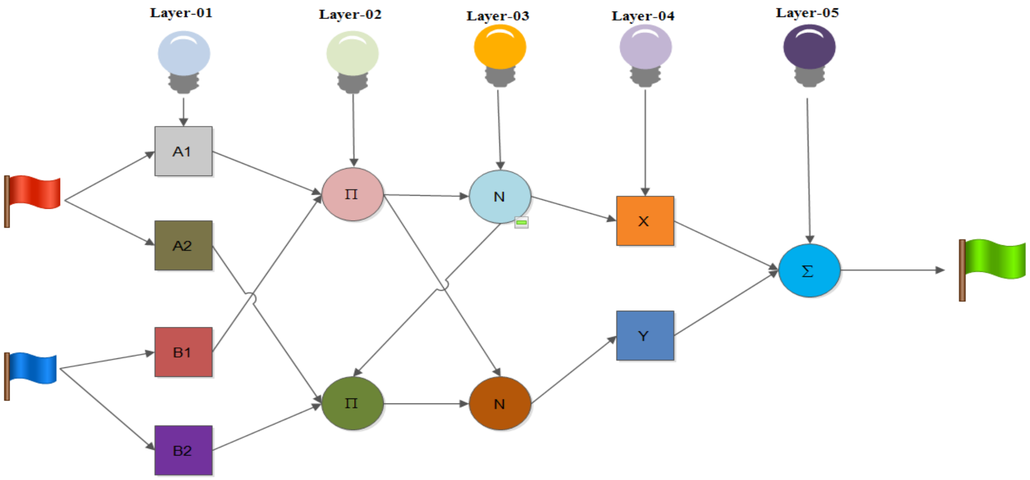

Fig 1 Fuzzy Equation Formation Flow Chart

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$$Overall\ output = O_{5,i} = f = \sum \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (9)$$

The circular nodes are the node which is always fixed, square node are very adaptive to situation and modification can be done only with nodes which are adaptive based on the needs of the user.

The adaptive neuro-fuzzy inference system is a hybrid based algorithm which is combined with both least square error and back-propagation techniques. In hybrid algorithm there will be 2 pass in the learning phase known as forward and backward pass. The nodes will reach till layer 4 and the parameters are found through least square in the forward pass. But in the case of back word pass the nodes are generated in backward position which are found through back-propagation. In the fixed parameter the found resultant is optimal. the back-propagation algorithm for supervised learning artificial neural networks using gradient descent.

In the fuzzy system it is very important in making decision while selecting the rules because it is very important to select a perfect rule if any mistake made during selection of rules it may lead to decreased accuracy of the fuzzy system. In this ANFIS approach grid partition or subtractive cluster can be used to create the basic structure of fuzzy inference system. The grid partition creates partitions with equal number of cells, decrease the partition boundary area, and it also minimises the number of partition neighbour. In this study the grid partition method computes all the possible rule base for membership function which lead to increase number of rules and also the computing time is also increased. In the other hand the subtractive cluster approach computes the cluster and its center of database utilizing one-pass algorithm. It is found that the subtractive clustering method involves lesser rule base and it is highly significant. The subtractive cluster approach is used in the beginning stage of the fuzzy model. The clear explanation and details about this method is analysed in the sections below.

3.3 Subtractive cluster method

Subtractive cluster method is utilized for generating tuned MF automatically in accordance to the domain. In this approach each data is obtained for probable data centre and the data set from the centre is normal so that they can be treated in equal range in all aspects. Let us consider a collection of n data points as $\{x\, x_{1,\,2,}\cdots.x_n\}$ in an M dimensional space. The P_i of the cluster center is defined as follows:

$$P_i = \sum_{j=1}^{n} \exp\left(\frac{-4}{r_a^2}.\| x_i - x_j \|^2\right) \qquad (10)$$

|| is the Euclidean distance of 2 data set, r_a which describes the neighbourhood effectually, n total number of data set. The data set outside the radius will have less influence in the potential. When the calculation for all the potential of all data set it will be found that the data set with higher potential is regarded as 1st cluster center. Where x_1^* and P_1^* is the location of 1st cluster center. After the selection of 1st cluster center the potential of all data set x_i is altered as:

$$P_i \Leftarrow P_i - P_1^*.\exp\left(\frac{-4}{r_b^2}.\| x_i - x_i^* \|^2\right) \qquad (11)$$

where r_b positive constant which identifies the neighbourhood with reduction in the potential. An amount of potential is reduced from the all data set based on the distance between the 1st cluster center, by this the data set nearer to the 1st cluster will have much lesser potential. The closely spaced cluster can be avoided where the r_b values are set higher than r_a and it is assumed that the values of values of r_b will be 1.20 times than that of r_a. after this the values of data are altered with the concept of equation 11, by which the data set next higher potential than the 1st is considered as 2nd cluster center. The potential of all the data set will be reduced again due to the distance of the 2nd cluster cenetr. After reaching the kth the potential of the data set will be described as:

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$$P_i \Leftarrow P_i - P_k^* \exp\left(\frac{-4}{r_b^2} . \| x_i - x_k^* \|^2\right) \tag{12}$$

Same process will be continued until the formation of new cluster and the modification in the data set will be continued until the end where it is satisfied and it is shown as:

$$P_k^* < \omega P_1^* \tag{13}$$

Where the ω is the threshold for the data set to reach the satisfied level in the cluster center and chances for data set to get rejected if the expected potential is not attained from data set. The value of ω is always 0.10. All the cluster center is obtained via subtractive cluster technique which is in the nature of prototypical data point which displays the characteristic nature of the system under consideration. All the cluster center will be used on the basis of rule to know the model type as well as to know the behaviour of the cluster system.

4. Model identifications

Let us consider a set of c cluster centers $\{x_1^*, x_2^* \cdots . x_c^*\}$, where M is the dimensional space, the N dimension are connected to input. The M, N are connected to the output. x_i* vector are composed of 2 parts location of cluster center in input space (y_i*) and the location of cluster center in the output space (z_i*) and represented as follows:

$$x_i^* = [y_i^*, z_i^*] \tag{14}$$

The cluster described by the fuzzy rule is described as, when the input is nearer to the cluster center in that case the output of the model is closer to the output of the cluster center. The stimulation is running using the MATLAB toolbox, and the output blocks of the simulation represents the results.

5. Proposed Model

This research paper tries to analyse the possible parameters in order to know the efficient way for external strengthening process. From various literature survey and guidelines certain parameters could be responsible for affecting the external wrapping system and especially affecting its efficacy. In order to obtain an efficient and significant model which will be capable enough in predicting the shear strength with limited parameter.

On the basis of literature survey it is found the efficacy of external strengthening system can affect the depth ratio of the shear span. the contribution of the concrete is different for RC beams in the case of shear resistance when compared to that of the RC beam without internal reinforcements. The different in the values are shown in the depth ratio where the value of depth ratio increases above 2.0 in this scenario depth ratio is known as the input parameter.

It is very important to lower the parameter in this case the fiber reinforcement polymer composites thickness, layers, and the modules of FRP will be merged because mentioned 3 sources will have direct effect on the shear contribution. These 3 are merged to give a new F value as follows:

$$F = n \times t_f \times E_f \tag{15}$$

Likewise the width of the fiber reinforced polymer and the principle fiber similarly have effect in the shear contribution directly. But in the case of spacing fiber reinforced composite the effect is inverse on the FRP. So these 3 combines to give a new input value P as follows:

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$$P = \frac{w_f}{s_f} \times (\sin\beta + \cos\beta) \quad (16)$$

Later after the process of merging the values the newly obtained parameter F and P are considered to be input parameter, where the V_f is known as the output parameter it is obtained through experimental process of FRP.

The different parameter which give different values of interval, the input in this case will be between the normal range of 0.1- 0.9 in response to equation 17. The aim aspect is to obtain a normal process which yields a same range of values for various input which may be helpful in speeding up the training and the scaling effect will be reduced at the same time.

$$x_{i,norm} = 0.1 + 0.8 \times \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (17)$$

After obtaining the normal values of input out of which almost 20 percent will be used for testing data set the remaining 80 percent will be utilized for training the model.

5.1 Selection of user defined parameters

The center of the cluster will be affected by certain parameters like influence range, accept ration, and the rejected ration. The squash factor(SF) is also one of the factor which is reasonable for affecting the center of the cluster. Which is used for multiplying the 1st cluster radius so this will be chose the neighbourhood cluster. It is known that when the SF is more the represent model is likely to choose the neighbourhood far away from the cluster center which will help in lesser number of rules and cluster center. The potential of the 1st cluster is shown with the accept ratio, the data from that will be regarded as point of the cluster, the reject ratio will be regarded as the fraction of the potential 1st cluster the values after that will be rejected. It is noted that if the number of reject ratio increase the rules or the cluster center number will be lowered. The radius has more effect on subtractive cluster method than that of its parameter of the cluster center. When value of the radius is small the cluster will be large in number as a fine model, if the value of the radius is large cluster will be lesser as a coarser model. Both model the model will not generalize properly. When the model fits the training dataset so well that kind of model will not fit the same way in testing dataset. This kind of thing is pointed out as overfitting. This research paper tries to find the influence of the radius of the cluster center and SF it is done on the basis of trial and error concept by making all the other parameters similar to their default values. This research tries to lower the errors in the result which is predicted already with the concept in training and testing dataset. For this the Adaptive Neuro-Fuzzy Inference System with various radius of cluster center and SF have been explored. Various factors involved in this model have be predicted to get the result in a good manner. It is found that the number of rules of the model is equivalent to the number of cluster of the model, and the subtractive cluster algorithm is responsible for determining the cluster center.

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left(\frac{|V_{f.ana} - V_{f.expt}|}{V_{f.expt}} \right) \quad (18)$$

$$R^2 = \frac{(n\sum(V_{f.ana}V_{f.ana}) - (\sum V_{f.expt})(\sum(V_{f.ana}))^2}{[n\sum(V_{f.expt}^2 - (\sum V_{f.expt}]^2 - [n\sum(V_{f.ana}^2 - (\sum V_{f.ana}]^2} \quad (19)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (V_{f.ana} - V_{f.expt})^2} \quad (20)$$

Where RSME (root mean square error), R^2 (coefficient of determinant), and MAPE (root mean square error).

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The good Adaptive Neuro-Fuzzy Inference System must have less values for the co-efficient of variance, root mean square error, and root mean square error for the entire dataset, alongside the ratio of the expected experiment result and coefficient of determinant must be closer to one of its value. There should be lesser difference in the different error, only them the prediction made will match the experiment result. The model with less number of rules are highly favourable, alongside with same performance in different error. The measurement of performance of the different Adaptive Neuro-Fuzzy Inference System model on different radius and squash factor. It is noted that the performance of different models increases with decrease in the value of radius and increase in number of rules. From the observation it is found that the different performance value obtained in the performance of the model 12 and 15 are same. The model 15 is taken for further investigation. The cluster center determined by the subtractive cluster which is capable for briefing the Fuzzy inference system and the rules for the model.

6 Result and Discussion

6.1 Comparison between the experimental data and present ANFIS model

The complete comparison was made with the predicted ANFIS model with the tensile contribution obtained through several experiments. The prediction perfectly correlated with the experiment result.

6.2. Tensile strength estimation using design guidelines and comparison with ANFIS model

In present times, many countries have tried out various approach for predicting the tensile contribution of the externally connected fiber reinforce polymer strengthening model. Various FIS diagram of ANFIS is shown below.

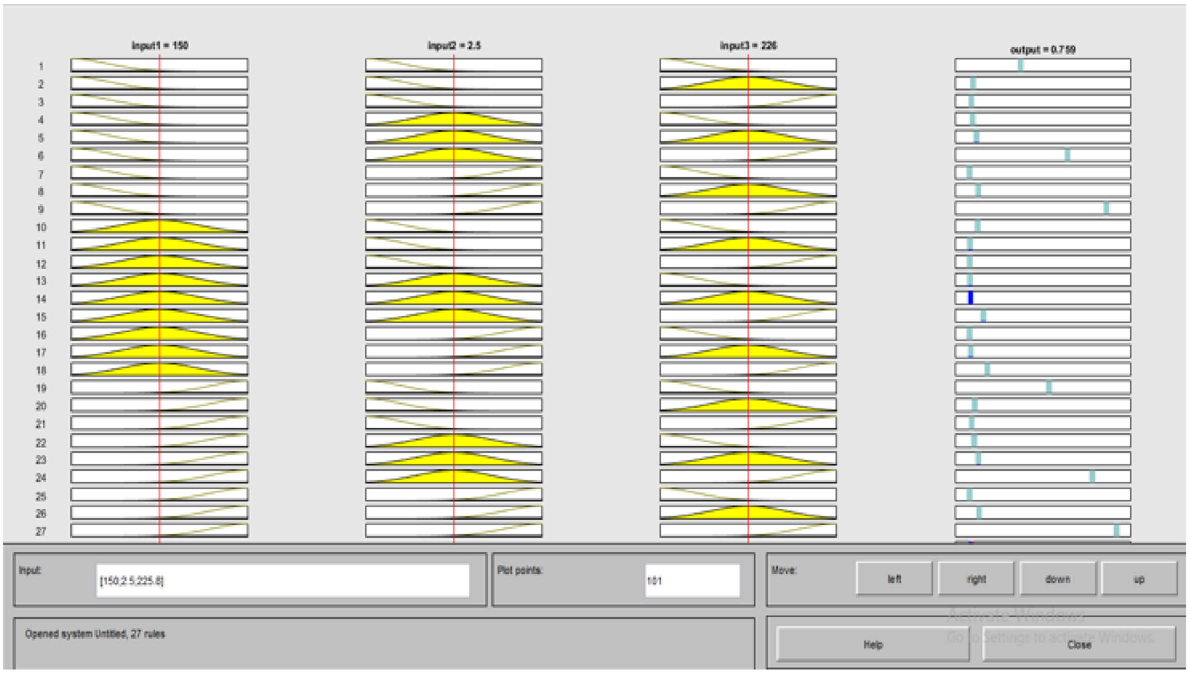

Fig 2 Performance of ANFIS in FCL (full container load)

Table 1 Values of FCL

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Spacing of Stirrups	FRP thickness	Tensile strength for FRP	FCL(kN)	ANFIS	%Variation
100	0	0	10	**11.2**	**12.0**
100	0	0	12.5	**11.2**	**10.4**
200	0	0	15	**17.5**	**16.0**
200	0	0	20	**17.5**	**12.5**
100	3	446.9	22.5	**23.7**	**5.3**
100	3	446.9	25	**23.7**	**5.2**
200	3	446.9	27.5	**28.7**	**4.3**
200	3	446.9	30	**28.7**	**4.3**
100	5	451.5	30	**31.2**	**4.0**
100	5	451.5	32.5	**31.2**	**4.0**
200	5	451.5	32.5	**33.7**	**3.6**
200	5	451.5	35	**33.7**	**3.7**

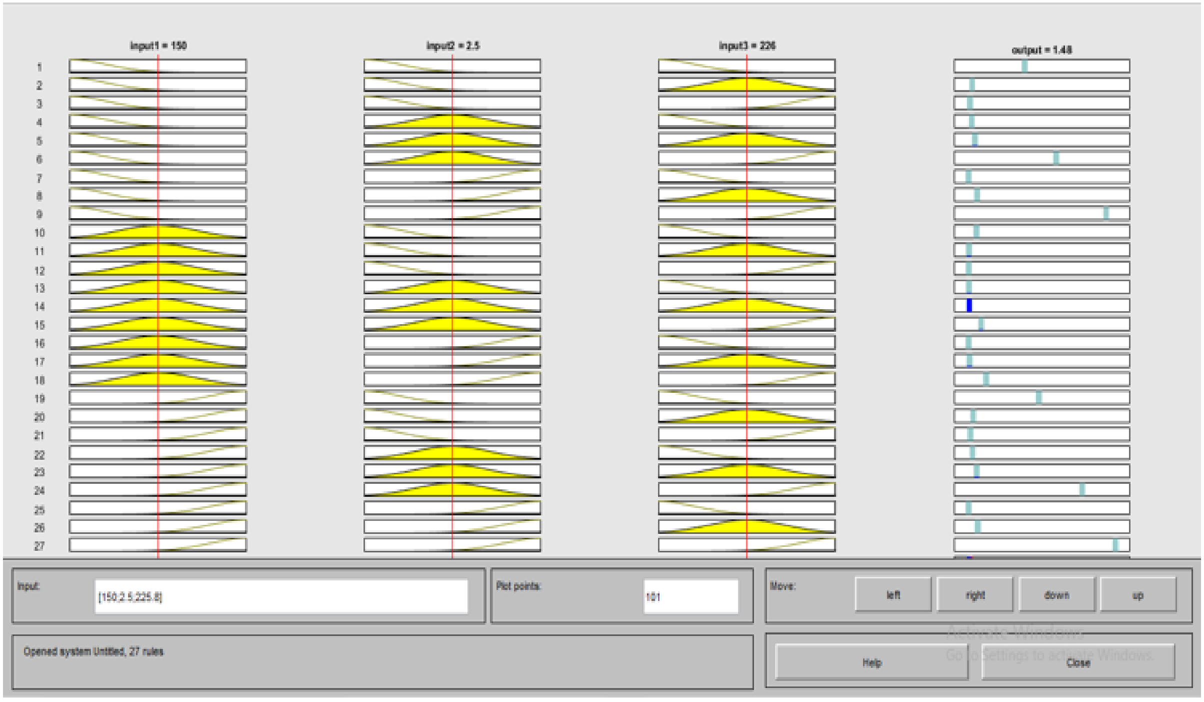

Fig 3 Performance of ANFIS in yield load

Table 2 Values of yield load

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Spacing of Stirrups	FRP thickness	Tensile strength for FRP	Yl(kN)	ANFIS	%VARIATION
100	0	0	25	**26.2**	**4.8**
100	0	0	27.5	**26.2**	**4.7**
200	0	0	30	**32.7**	**9.0**
200	0	0	35.5	**32.7**	**7.8**
100	3	446.9	42.5	**46.2**	**8.7**
100	3	446.9	50	**46.2**	**7.6**
200	3	446.9	54.5	**57.2**	**4.9**
200	3	446.9	60	**57.2**	**4.6**
100	5	451.5	64.5	**66.2**	**2.6**
100	5	451.5	68	**66.2**	**2.6**
200	5	451.5	70	**71.2**	**1.7**
200	5	451.5	72.5	**71.2**	**1.8**

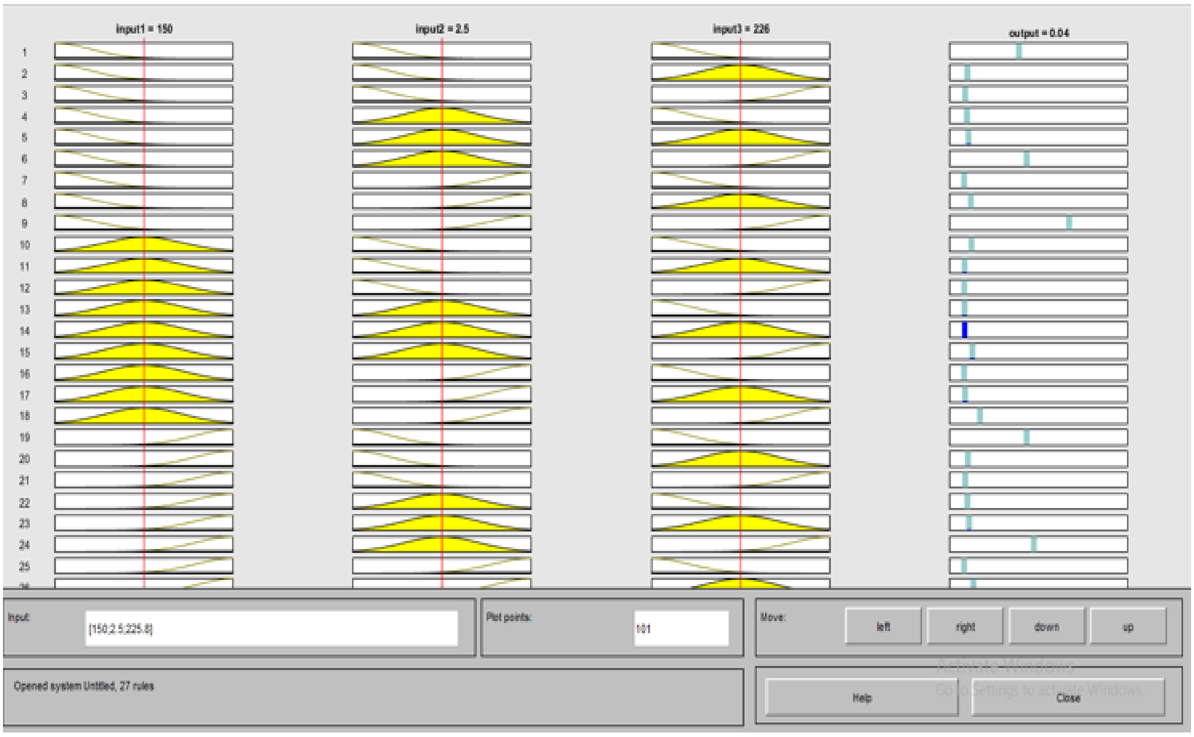

Fig 4 Performance of ANFIS in Unlimited load

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Table 3 Values of unlimited load

Spacing of Stirrups	FRP thickness	Tensile strength for FRP	ul(kN)	ANFIS	%Variation
100	0	0	50	**53.7**	**7.4**
100	0	0	57.5	**53.7**	**3.8**
200	0	0	60	**62.5**	**4.2**
200	0	0	65	**62.5**	**2.5**
100	3	446.9	90	**95.2**	**5.7**
100	3	446.9	100.5	**95.2**	**5.3**
200	3	446.9	110	**115**	**4.5**
200	3	446.9	120.5	**115**	**4.6**
100	5	451.5	130	**132**	**1.5**
100	5	451.5	135	**132**	**2.2**
200	5	451.5	142.5	**144**	**1.1**
200	5	451.5	145	**144**	**6.9**

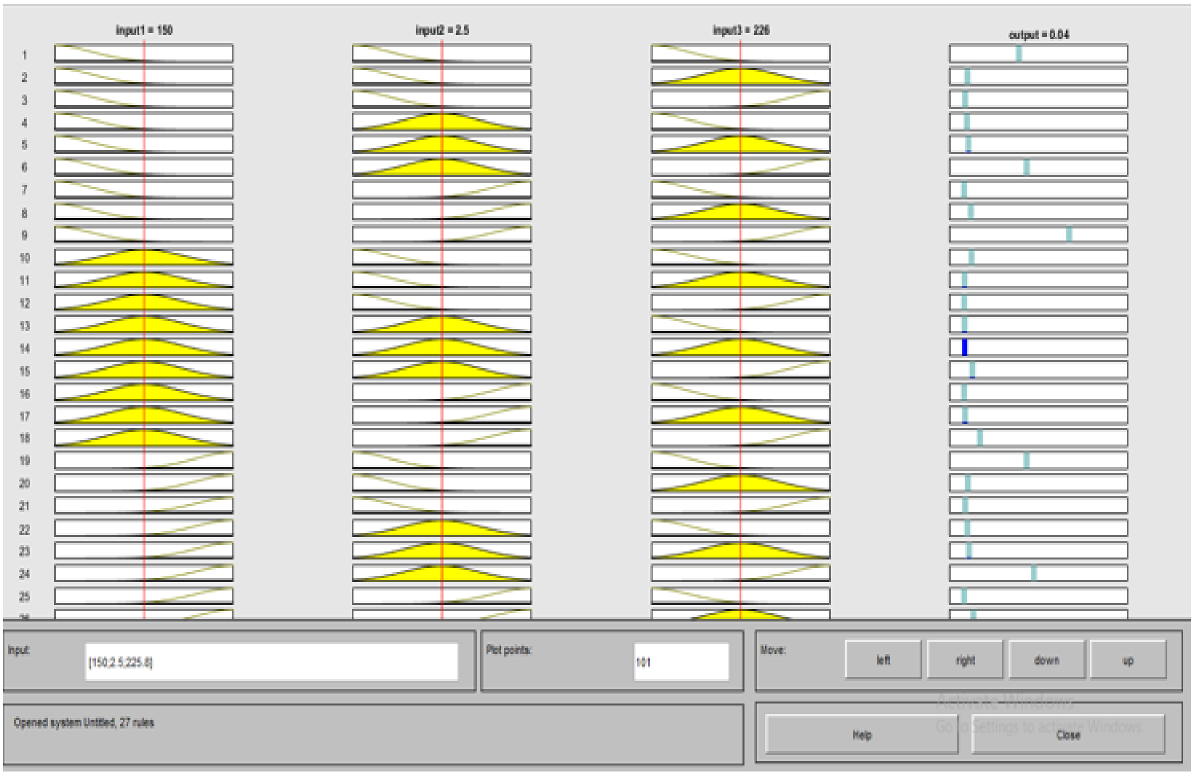

Fig 5 Definition of ANFIS in full container load

Table 4 Values of ANAFIS performance in FCL

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Spacing of Stirrups	FRP thickness	Tensile strength for FRP	Def. @ FCL (mm)	ANFIS	%Variation
100	0	0	0.95	**1**	**-5.3**
100	0	0	1.05	**1**	**4.8**
200	0	0	1.12	**1.14**	**-1.8**
200	0	0	1.16	**1.14**	**1.7**
100	3	446.9	1.28	**1.31**	**-2.3**
100	3	446.9	1.34	**1.31**	**2.2**
200	3	446.9	1.48	**1.56**	**-5.4**
200	3	446.9	1.64	**1.56**	**4.9**
100	5	451.5	1.86	**1.98**	**-6.5**
100	5	451.5	2.1	**1.98**	**5.7**
200	5	451.5	2.46	**2.78**	**-13.0**
200	5	451.5	3.1	**2.78**	**10.3**

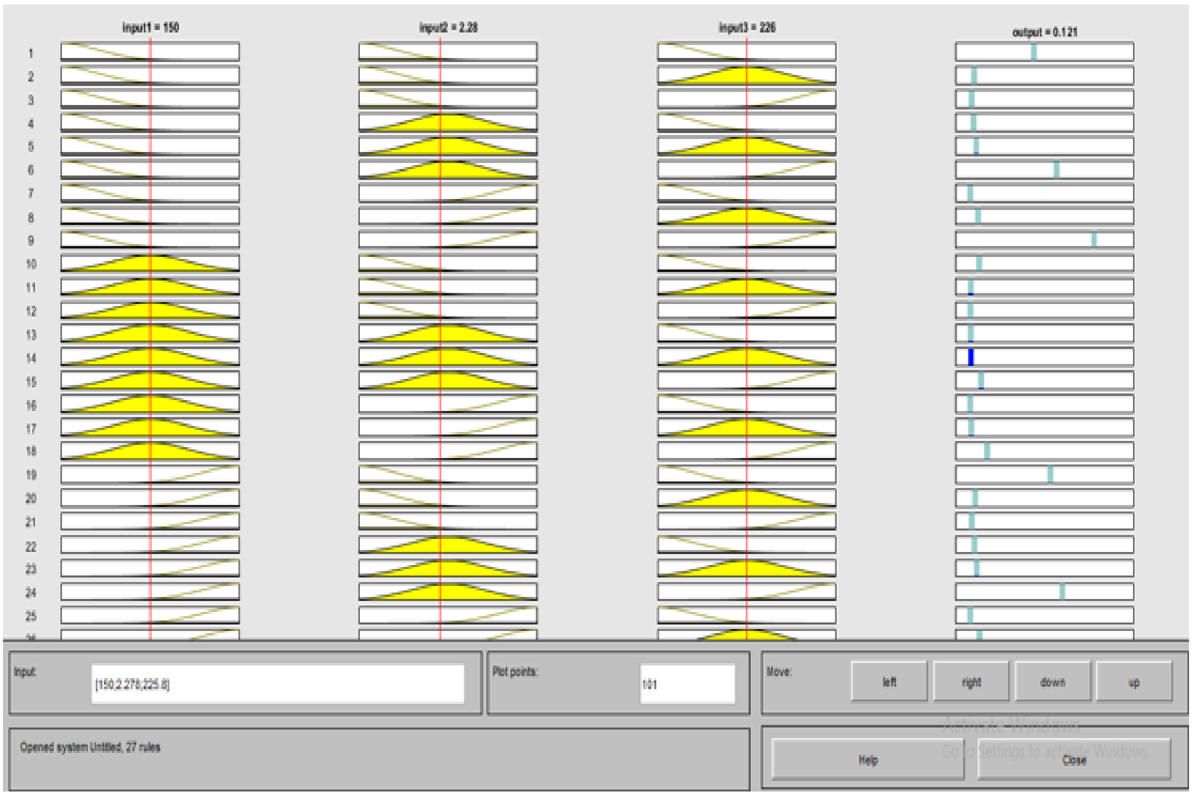

Fig 6 Definition of ANFIS in yield load

Table 5 Values of ANAFIS performance in yield load

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Spacing of Stirrups	FRP thickness	Tensile strength for FRP	Def. @ YL (mm)	ANFIS	%Variation
100	0	0	2.6	**2.72**	**-4.6**
100	0	0	2.85	**2.72**	**4.6**
200	0	0	3.2	**3.42**	**-6.9**
200	0	0	3.65	**3.42**	**6.3**
100	3	446.9	3.98	**4.08**	**-2.5**
100	3	446.9	4.18	**4.08**	**2.4**
200	3	446.9	4.33	**4.47**	**-3.2**
200	3	446.9	4.62	**4.47**	**3.2**
100	5	451.5	5.16	**5.49**	**-6.4**
100	5	451.5	5.82	**5.49**	**5.7**
200	5	451.5	6.28	**6.56**	**-4.5**
200	5	451.5	6.85	**6.56**	**4.2**

Conclusion

In this study the prediction of tensile contribution of fiber-reinforced polymers (FRP) for the wrapped reinforced concrete (RC) beams using an adaptive neuro-fuzzy inference system (ANFIS). For this method the training and testing for the ANFIS input and output was done. Selecting the ANFIS for FRP was crucial because of its kind of parameter because sometimes it was considered as the combination of ANN and FIS model it should overcome the limitation to yield better result. From several examination and analysis made with Adaptive Neuro-Fuzzy Inference System and the test results they both have correlated with each other. The obtained result was compared with the 7 predicted guidelines and it is found that the predicted result is almost same as the obtained one. The ANFIS is more accurate and reliable then the other model. In this study the training of the ANFIS is done with wide range of input data and if it is treated with input which is beyond the range it may be difficult to gain the same amount of accuracy in the result and performance. The result from this current study shows that the Adaptive Neuro- Fuzzy Interference System(ANFIS) can be used as the alternative for predicting the shear power of the fiber-reinforced composite(FRP).

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